NBA Player Attributes On and Off Court Exploratory Data Analysis

September 28, 2019

1 Exploratory Data Analysis of NBA Player Attributes On and Off the Court

2 Dataset Description

The dataset I used for this project is from the Kaggle data repository (https://www.kaggle.com/noahgift/social-power-nba). The dataset is titled "Social Power NBA" and contains performance, salary, and twitter data for 100 NBA players of the 2016-2017 season.

2.0.1 Problem Statement

The social aspect of the NBA is arguably the most prominent of the major American sports. Including twitter data in this dataset with performance and salary statistics, allows for a more holistic view of a players impact on an organization. In a game where chemistry is tantamount and determining the appropriate salary based on the impact of a player is vital to assess personnel changes within a team, this dataset can provide the a subset of these data (100 player cross section of the NBA) to elucidate these relationships.

Do players make more money because they have a stronger twitter following or does increased social activity result in poor performance due to off-court distractions? Ultimately, how can the on and off court impact of a player be valued for management to make better decisions in terms of winning, who to play, and how much to pay them?

```
In [19]: # Load libraries
         import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt

         # Load NBA dataset
         nba = pd.read_csv("~/Documents/UW Data Science Certificate/Methods for Data Analysis/r
```

3 Examine the data

In taking a first look at the data, I obtained the shape and datatypes of the dataset. Next, I print out the first five rows of the data to get an idea for how the table is structured. Then, I listed the columns for reference and calculated the summary statistics for each column in the dataset.

```
In [178]: # Print the shape and datatypes of the dataset
          print(nba.shape)
          print(nba.dtypes)
          # Get the first five rows of the dataset
          nba.head()
          # List the column names in the dataset
          nba.columns
          # Get the summary statistics for the nba dataset
          nba.describe()
```

```
(100, 66)
PLAYER_ID                            int64
PLAYER_NAME                         object
TEAM_ID                              int64
TEAM_ABBREVIATION                   object
AGE                                  int64
GP                                   int64
W                                    int64
L                                    int64
W_PCT                              float64
MIN                                float64
OFF_RATING                         float64
DEF_RATING                         float64
NET_RATING                         float64
AST_PCT                            float64
AST_TO                             float64
AST_RATIO                          float64
OREB_PCT                           float64
DREB_PCT                           float64
REB_PCT                            float64
TM_TOV_PCT                         float64
EFG_PCT                            float64
TS_PCT                             float64
USG_PCT                            float64
PACE                               float64
PIE                                float64
FGM                                  int64
FGA                                  int64
FGM_PG                             float64
FGA_PG                             float64
FG_PCT                             float64
                                    ...
DEF_RATING_RANK                      int64
NET_RATING_RANK                      int64
AST_PCT_RANK                         int64
AST_TO_RANK                          int64
```

```
AST_RATIO_RANK                         int64
OREB_PCT_RANK                          int64
DREB_PCT_RANK                          int64
REB_PCT_RANK                           int64
TM_TOV_PCT_RANK                        int64
EFG_PCT_RANK                           int64
TS_PCT_RANK                            int64
USG_PCT_RANK                           int64
PACE_RANK                              int64
PIE_RANK                               int64
FGM_RANK                               int64
FGA_RANK                               int64
FGM_PG_RANK                            int64
FGA_PG_RANK                            int64
FG_PCT_RANK                            int64
CFID                                   int64
CFPARAMS                              object
WIKIPEDIA_HANDLE                      object
TWITTER_HANDLE                        object
SALARY_MILLIONS                      float64
PTS                                  float64
ACTIVE_TWITTER_LAST_YEAR               int64
TWITTER_FOLLOWER_COUNT_MILLIONS      float64
salary_bin                          category
twitter_bin                         category
counts                                 int64
Length: 66, dtype: object
```

Out[178]:

```
          PLAYER_ID       TEAM_ID         AGE          GP           W  \
count  1.000000e+02  1.000000e+02  100.000000  100.000000  100.000000
mean   3.026027e+05  1.610613e+09   27.510000   62.440000   33.020000
std    4.237828e+05  8.788445e+00    3.935066   21.261869   15.421342
min    1.717000e+03  1.610613e+09   20.000000    2.000000    0.000000
25%    2.011780e+05  1.610613e+09   25.000000   55.500000   22.750000
50%    2.023305e+05  1.610613e+09   27.000000   72.000000   35.000000
75%    2.034582e+05  1.610613e+09   30.000000   77.000000   43.250000
max    1.627848e+06  1.610613e+09   39.000000   82.000000   65.000000

                L       W_PCT         MIN  OFF_RATING  DEF_RATING    ...     \
count  100.000000  100.000000  100.000000  100.000000  100.000000    ...
mean    29.420000    0.507010   26.391000  107.728000  105.946000    ...
std     12.726478    0.159991    9.221222    5.157324    4.165889    ...
min      1.000000    0.000000    3.300000   86.800000   93.000000    ...
25%     21.000000    0.416000   19.450000  104.275000  103.625000    ...
50%     30.500000    0.506500   29.700000  107.150000  106.000000    ...
75%     37.250000    0.626250   33.900000  110.275000  108.525000    ...
max     55.000000    0.824000   37.800000  124.200000  118.300000    ...
```

```
         FGA_RANK  FGM_PG_RANK  FGA_PG_RANK  FG_PCT_RANK   CFID  \
count  100.000000   100.000000   100.000000   100.000000  100.0
mean   138.350000   110.350000   128.700000   133.120000    5.0
std    136.383919   112.122171   129.410591    94.382553    0.0
min      1.000000     1.000000     1.000000     1.000000    5.0
25%     28.750000    28.750000    28.750000    47.000000    5.0
50%     82.000000    68.000000    70.500000   132.000000    5.0
75%    217.250000   163.000000   188.500000   198.500000    5.0
max    484.000000   465.000000   483.000000   355.000000    5.0

       SALARY_MILLIONS         PTS  ACTIVE_TWITTER_LAST_YEAR  \
count       100.000000  100.000000                100.000000
mean         11.290120   15.174200                  0.930000
std           8.789342    7.319374                  0.256432
min           0.310000    1.500000                  0.000000
25%           2.842500    9.225000                  1.000000
50%          10.820000   14.550000                  1.000000
75%          18.400000   20.650000                  1.000000
max          30.960000   31.600000                  1.000000

       TWITTER_FOLLOWER_COUNT_MILLIONS  counts
count                       100.000000   100.0
mean                          1.516579     1.0
std                           4.345148     0.0
min                           0.000000     1.0
25%                           0.048000     1.0
50%                           0.244000     1.0
75%                           0.857750     1.0
max                          37.000000     1.0

[8 rows x 59 columns]
```

4 Observation 1: Salary is highly correlated with points per game and Twitter followers. Wins and points per game also have a strong relationship

Using a correlation matrix, I looked into a few potential relationships in this dataset. I created a correlation matrix with the following attributes: Wins, Points per game, Age, Offensive Rating, Defensive Rating, Salary (millions), and Twitter Followers (millions).

I plotted these correlations as a heatmap and there are some notable relationships such as the strong correlation between Points per Game and Salary, Points per Game and Wins, and Twitter Followers and Salary. These correlations suggest that players get paid more for scoring and in turn have a stronger following on Twitter due to their impact on their teams performance.

In [167]:
```
# Generate a correlation matrix from the dataset
nba_corr = nba[['W', 'PTS', 'AGE', 'OFF_RATING', 'DEF_RATING', 'SALARY_MILLIONS', 'TW
```

```
# Print the correlation matrix
nba_corr
```

Out[167]:

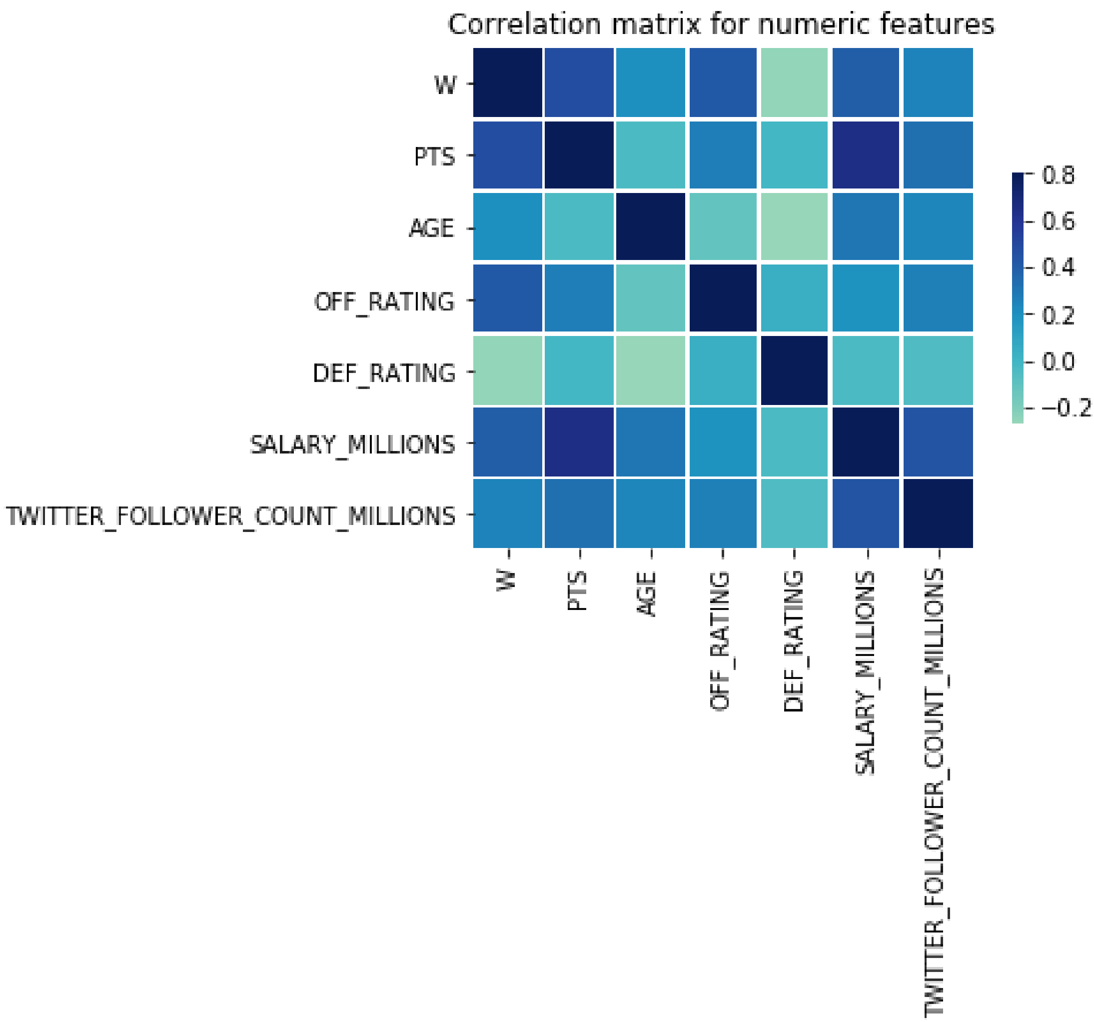
```
                                       W       PTS       AGE  OFF_RATING  \
W                               1.000000  0.475038  0.203069    0.422244
PTS                             0.475038  1.000000 -0.031333    0.271257
AGE                             0.203069 -0.031333  1.000000   -0.104785
OFF_RATING                      0.422244  0.271257 -0.104785    1.000000
DEF_RATING                     -0.253202 -0.004879 -0.266586    0.039845
SALARY_MILLIONS                 0.391831  0.647343  0.301526    0.188706
TWITTER_FOLLOWER_COUNT_MILLIONS 0.250282  0.327236  0.245081    0.265210

                                DEF_RATING  SALARY_MILLIONS  \
W                                -0.253202         0.391831
PTS                              -0.004879         0.647343
AGE                              -0.266586         0.301526
OFF_RATING                        0.039845         0.188706
DEF_RATING                        1.000000        -0.035141
SALARY_MILLIONS                  -0.035141         1.000000
TWITTER_FOLLOWER_COUNT_MILLIONS  -0.046075         0.443932

                                TWITTER_FOLLOWER_COUNT_MILLIONS
W                                                      0.250282
PTS                                                    0.327236
AGE                                                    0.245081
OFF_RATING                                             0.265210
DEF_RATING                                            -0.046075
SALARY_MILLIONS                                        0.443932
TWITTER_FOLLOWER_COUNT_MILLIONS                        1.000000
```

In [168]:

```
# Generate a heat map based on the correlation matrix created above
sns.heatmap(nba_corr, vmax=.8, center=0,
            square=True, cmap = "YlGnBu", linewidths=.25, cbar_kws={"shrink": .5})
plt.title('Correlation matrix for numeric features in the NBA Social Power dataset')
plt.yticks(rotation='horizontal') # rotate y tick marks
plt.xticks(rotation='vertical') # rotate x tick marks
```

Out[168]:

```
(array([0.5, 1.5, 2.5, 3.5, 4.5, 5.5, 6.5]),
 <a list of 7 Text xticklabel objects>)
```



5 Observation 2: Strong relationship observed between wins and field goals attempted

I found that one of the stronger relationships was between Wins and Field Goals Attempted. The strong positive correlation between these two variables suggests that the more field goal attempts taken by a player results in more wins for their team. In some ways this makes sense, with more shot attempts resulting in more points and ultimately a higher chance of winning. However, from a coaching perspective, it's usually emphasized to have better shot selection in taking more high percentage shots. These data alone may decieve a player into just generally shooting more because the attempts correlate with wins.

```
In [1]: # Scatter plot of wins vs field goals attempted
        import seaborn as sns
        sns.lmplot(x = 'W', y = 'FGA',
```

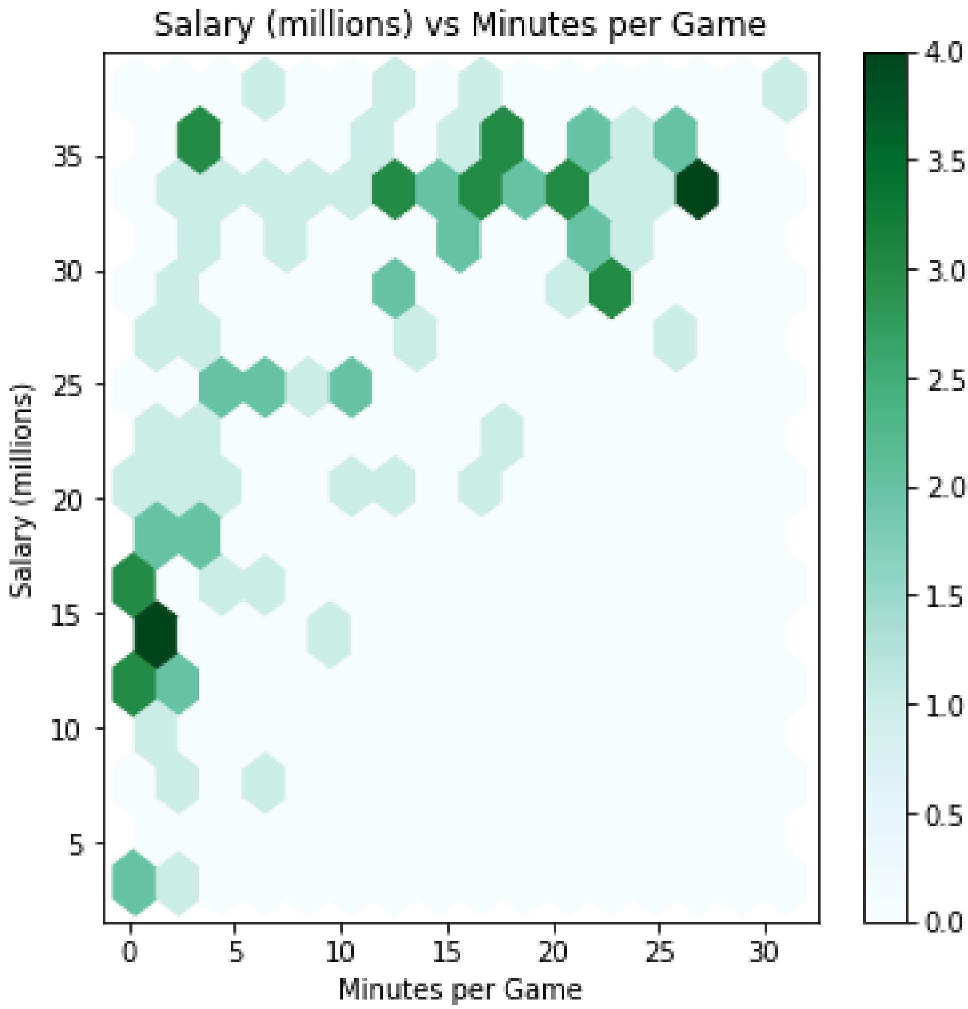
```
                 data = nba,
                 palette="hls",
                 scatter_kws={'alpha':0.3},
                 fit_reg = True)
plt.xlabel('Wins') # Label the x axis
plt.ylabel('Field Goal Attempts') # Label the y axis
plt.title('Wins vs. Field Goal Attemps') # Give plot a title


---------------------------------------------------------------------------

NameError                                 Traceback (most recent call last)

<ipython-input-1-2b2adf9f92b5> in <module>()
      1 # price
----> 2 salary = salary_wiki_twitter.loc[:, 'SALARY']
      3 # plot distributions
      4 _ = pyplot.hist(salary)
      5 pyplot.show()


NameError: name 'salary_wiki_twitter' is not defined
```

6 Observation 3

Looking at the relationship between Salary and Minutes per Game elucidates a few groups of contract types. In the hexbin plot below, there are two major pockets of data. There are quite a few players in the bottom left corner of the plot in which players are playing 5 minutes or less per game but they are still making at least 10 million. The other pocket of data is in the upper right hand corner of the plot, where players are making over 30 million dollars and are playing at least 15 minutes per game.

The trend observed in the upper part of the plot, where players are making more money and playing more minutes, is expected. From a management standpoint, you don't want to pay players a high salary and not play them. However, this concept is what makes the bottom left part of the plot more interesting. Why are players getting paid at least 10 million dollars but are not playing many minutes at all? This could be the result of the high minimum salary that the NBA has. However, this trend looks like it would be something worth looking into. Are organizations overvaluing these players? If so, based on what metrics?

```
In [173]: # Generate hexbin plot comparing Salary and minutes per game
          ax = plt.figure(figsize=(6, 6)).gca() # define axis
          nba.plot.hexbin(x = 'SALARY_MILLIONS', y = 'MIN', gridsize = 15, ax = ax)
          ax.set_title('Salary (millions) vs Minutes per Game') # Give the plot a main title
          ax.set_ylabel('Salary (millions)')# Label y axis
          ax.set_xlabel('Minutes per Game') # Label x axis

Out[173]: Text(0.5,0,'Minutes per Game')
```



7 Observation 4

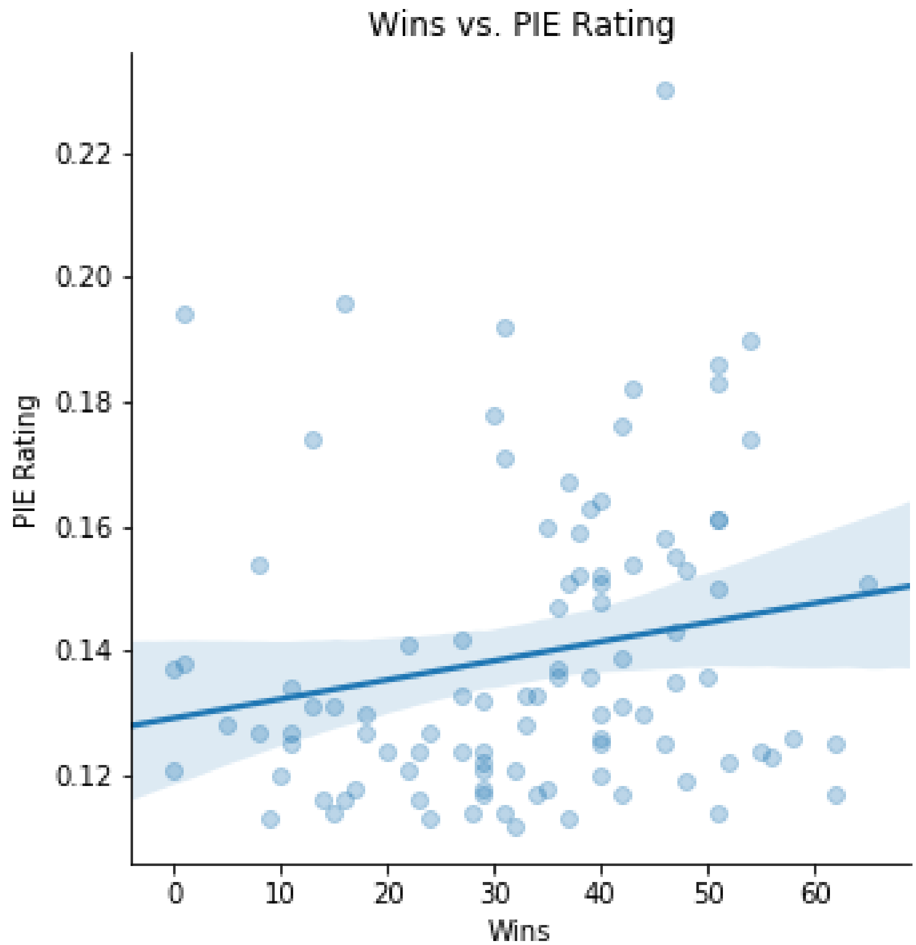
As data continues to be collected at such a high rate in the NBA, the creation of new statistics to describe a players impact are created in order to make more data driven decisions. One of these statistics that is commonly used by NBA.com is called PIE, a metric that measures the percentage of game events (Points, Rebounds, Assists, etc) the player achieved in a game. This metric typically trends with wins (I assessed this correlation below) but I was curious to see if the PIE metric was related to the number of twitter followers a player has.

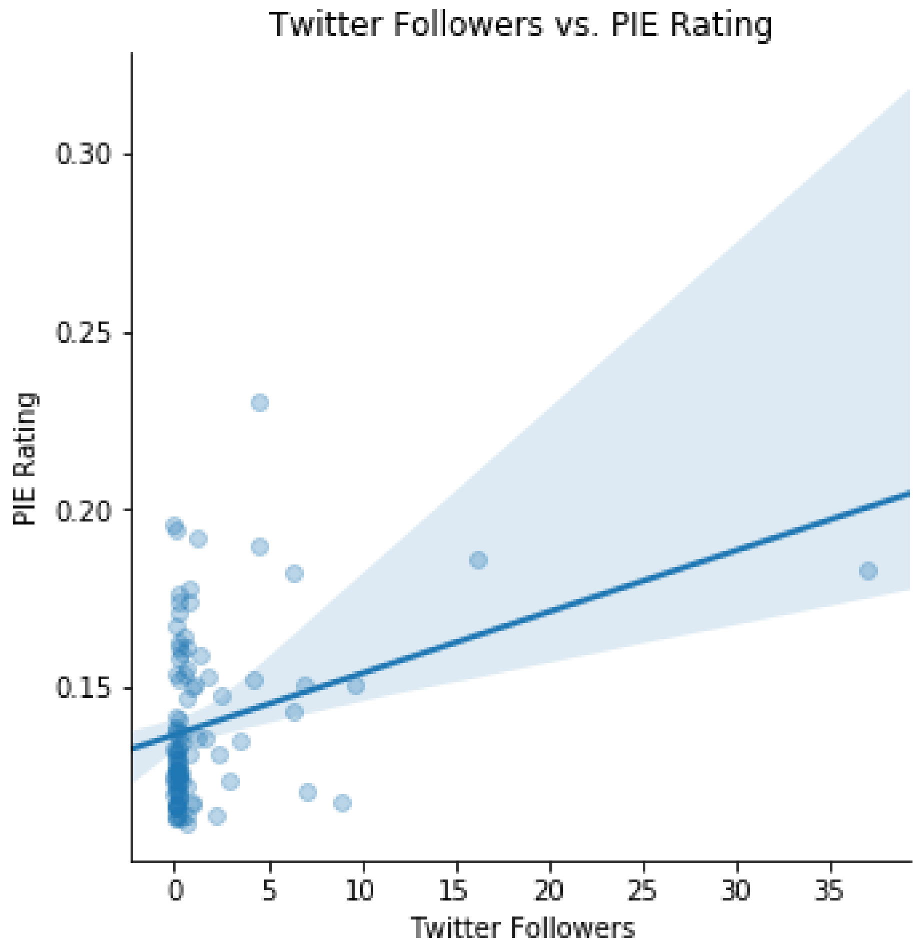
Below, the first scatter plot shows that there is a weaker relationship between the PIE rating and wins than I expected. Although the trend still weakly holds, I expected there to be a stronger correlation.

The second scatter plot displays a relationship between twitter followers and PIE rating but the trend only holds with players with a higher number of twitter followers. These look like outliers that are making the correlation appear better than it really is. The points clustered on left part of the plot are made up with players that have do not have many twitter followers but a variable

PIE rating. This trend makes sense because it would be expected to see better players have more Twitter followers and also have a high PIE rating but there also are players who have higher PIE ratings without having as many Twitter followers.

```
In [175]: # Scatter Plot comparing wins and PIE rating
          import seaborn as sns
          sns.lmplot(x = 'W', y = 'PIE',
                     data = nba,
                     palette="hls",
                     scatter_kws={'alpha':0.3},
                     fit_reg = True)
          plt.xlabel('Wins') # Label x axis
          plt.ylabel('PIE Rating') # Label y axis
          plt.title('Wins vs. PIE Rating') # Give plot a title

          # Scatter Plot
          import seaborn as sns
          sns.lmplot(x = 'TWITTER_FOLLOWER_COUNT_MILLIONS', y = 'PIE',
                     data = nba,
                     palette="hls",
                     scatter_kws={'alpha':0.3},
                     fit_reg = True)
          plt.xlabel('Twitter Followers') # Label x axis
          plt.ylabel('PIE Rating') # Label y axis
          plt.title('Twitter Followers vs. PIE Rating') # Give plot a title

Out[175]: Text(0.5,1,'Twitter Followers vs. PIE Rating')
```


Wins vs. PIE Rating
PIE Rating
0.22
0.20
0.18
0.16
0.14
0.12
0
10
20
30
40
50
60
Wins



8 Summary

In my initial exploration of this dataset, I have identified a few relationships that can build a foundation for further data analysis. My first step was to get a feel for how the data were structured in the table and obtain the summary statistics. Next, I used a heatmap to visualize the high level correlations that I thought would be important in the dataset.

I used a scatter plot to display the relationship between Field Goal Attempts and Wins. This trend makes sense in terms of having a higher chance of winning but still was interesting to consider how this could affect coaching decisions, especially when coaches typically emphasize good shot selection.

I generated a hexbin plot to look at how the Salary and Minutes per Game may be the result of a high minimum salary in NBA contracts and how this plot can help identify two major groups of players and their contract / playing situations.

Finally, I took a look at one of the newer statistics that has been created to evaluate players, the PIE rating. According to NBA.com, this metric should correlate with wins but I was surprised to see a weak correlation between the two in this dataset. Furthermore, the PIE rating and Twitter

Followers relationship seemed to be skewed by a few outliers but can elucidate good players who have less followers on social media and players with similar PIE rating but have fewer twitter followers.

Overall, these trends provide more context to a players impact than just the performance statistics alone. The observations I've laid out above provide a good starting point to dig further into the data and generate predictive models to project a player's impact on a team, trade value, or social impact.